International Journal of Multidisciplinary Engineering in Current Research - IJMEC
Volume 10, Issue 5, May-2025, http://ijmec.com/, ISSN: 2456-4265

Exploring Trajectory Prediction through Machine Learning Methods

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Abstract: This project presents a machine learning-based approach for predicting the future trajectory of users by analyzing their previous movement patterns. Utilizing advanced algorithms such as Long Short-Term Memory (LSTM) networks and Sequence-to-Sequence (Seq2Seq) models, the system aims to forecast the next location(s) of a user based on historical GPS data. Accurate location prediction has significant applications in 5G networks, where allocating the nearest cloud resources to a user can drastically reduce latency and enhance user experience. The Geolife dataset, which consists of real-world GPS trajectories including latitude, longitude, and user ID, was used to train the model. Experimental results show that the proposed method achieves high prediction accuracy, with an LSTM-Seq2Seq model outperforming traditional algorithms like GRU, demonstrating lower mean squared error rates and better trajectory forecasting performance.

I. INTRODUCTION

In the age of 5G and edge computing, accurately predicting the next location of a user is critical for efficient network resource allocation and improved mobile application performance. Traditional methods such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) struggle to scale effectively with large datasets. To address this, the project introduces a predictive framework using Recurrent Neural Networks (RNN), specifically Long Short-Term Memory (LSTM) networks enhanced with Seq2Seq architecture. LSTM networks are capable of retaining important data from previous time steps, while Seq2Seq models provide a robust method for generating future sequences. The project is implemented using the Geolife dataset, which includes sequences of latitude and longitude data from multiple users. This approach enables real-time trajectory forecasting, contributing to advancements in smart navigation, traffic management, and next-gen mobile services.

II. LITEARTURE SURVEY

Trajectory prediction has gained significant importance in recent years due to its wide applications in transportation systems, mobile networking, smart cities, and location-based services. Various machine learning and deep learning techniques have been explored to enhance the accuracy and reliability of predicting user or object movement based on historical trajectory data.

1. Traditional Machine Learning Approaches: Earlier models such as **K-Nearest Neighbors (KNN)** and **Support Vector Machines (SVM)** were widely used for trajectory classification and prediction. While these methods provided initial success, their effectiveness declined with large-scale datasets due to their inability to capture temporal dependencies in sequential data.

2. Markov and Probabilistic Models: **Hidden Markov Models (HMM)** and **Bayesian networks** have been applied to model user mobility patterns. These approaches rely on probabilistic transitions between states (locations) but are limited by their assumptions of independence and memoryless transitions.

3. Recurrent Neural Networks (RNNs): RNNs introduced the capability to model sequential data by maintaining a hidden state over time. However, standard RNNs struggle with long-term dependencies due to vanishing gradients.

4. Long Short-Term Memory (LSTM): To overcome the limitations of RNNs, **LSTM**

networks were introduced. LSTM's gated architecture allows it to remember long-term dependencies, making it suitable for sequential tasks such as time-series forecasting and trajectory prediction. Many researchers have shown improved results using LSTM for GPS-based location forecasting.

5. Sequence-to-Sequence (Seq2Seq) Models: Originally proposed for machine translation, **Seq2Seq models** have found applications in trajectory prediction by encoding input sequences (past movements) and decoding future sequences (future movements). Combining Seq2Seq with LSTM further enhances the model's ability to forecast complex and non-linear spatial patterns.

6. Deep Spatio-Temporal Models: Recent advancements include hybrid models combining LSTM with **Convolutional Neural Networks (CNNs)**, **Graph Neural Networks (GNNs)**, and **Attention mechanisms** to learn spatial dependencies along with temporal sequences. These models have shown high promise in urban mobility and traffic forecasting.

7. Real-World Dataset Utilization: Datasets such as **Geolife**, **T-Drive**, and **Foursquare** have become standard benchmarks in evaluating trajectory prediction models. The Geolife dataset, used in this project, provides real-life GPS traces collected from users over long periods, capturing varied movement behaviors.

These advancements collectively demonstrate that trajectory prediction has evolved from simple statistical models to complex deep learning architectures capable of handling high-dimensional, sequential spatial data.

III. PROPOSED METHOD

In this paper author is describing concept to predict next location of single or multiple users by training trajectories (users previous location movement latitude and longitude) of their previous locations using RNN (Recurrent Neural Networks) advance version called LSTM (Long Term Short Term Memory) and Seq2Seq (sequence to sequences) algorithms. Predicting location of users plays an important role for 5G Internet networks as network service providers need to allocate nearest resources (cloud servers who take users mobile heavy computation task and process that request and send result back to mobile, if nearest cloud allocate to user then response will be faster and this nearest allocation can be done if users next locations can be predicted) to users to process their mobile request data.

Earlier algorithms such as KNN, SVM etc can predict user's location but their performance will not be efficient when data size goes beyond limit. To overcome from this problem author is using combination of advance LSTM and Seq2Seq algorithms which is very much efficient in prediction and fast processing.

LSTM algorithm contains multiple copies of memory from training data and each copy consists of input, output and forget cells. Input contains input data and output contains output data and if output is not related or new output is better than old output then forgot cell contains old output data. This process continues till all training data allocated to input and output cells. New test location data will be applied on LSTM train output cell to predict future location.

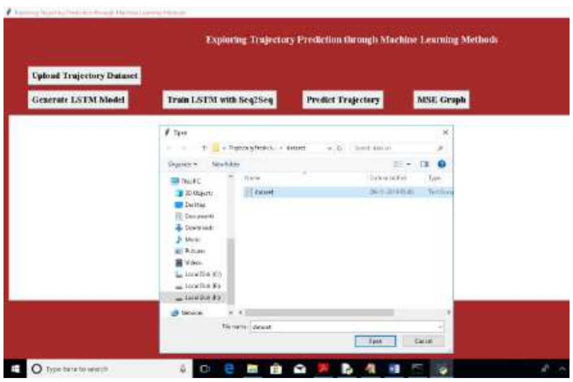
Seq2Seq algorithms can be included inside LSTM algorithm which can help in predicting sequences of future locations from train data. Seq2Seq algorithm consists of two parts called Encoder and Decoder. Encoder will convert training data into two dimensional array and Decoder will predict next sequences from those two dimensional array.

To implement above concept author is using Geolife real life trajectory movement dataset which consist of user's movement latitude, longitude and users id and each user has 9 locations. By training this dataset with LSTM and Seq2Seq we can predict next sequences of user's locations.

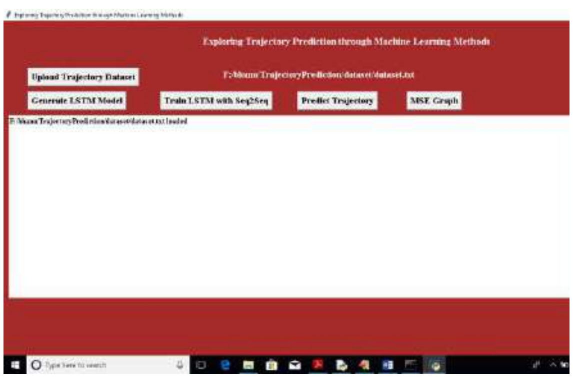
IV. RESULTS

To run this project double click on 'run.bat' file to get below screen

Click on ‘Upload Trajectory Dataset’ button to upload dataset



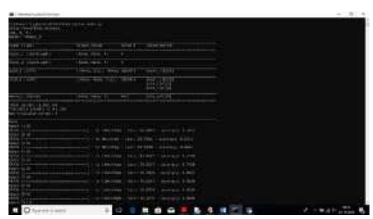
After uploading dataset will get below screen



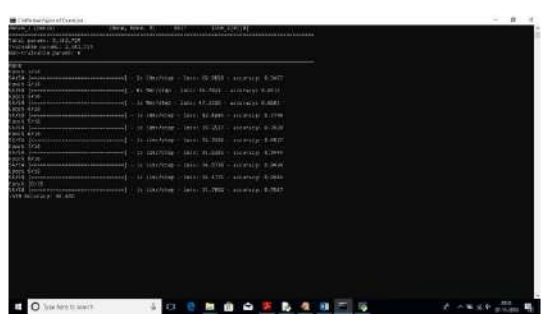
Now click on ‘Generate LSTM Model’ button to initialize LSTM algorithm or to generate model with number of features given in dataset

In above screen we can see LSTM model generated. Now click on ‘Train LSTM with Seq2Seq’ button to train uploaded dataset with initialize LSTM and Seq2Seq Encoder and Decoder object

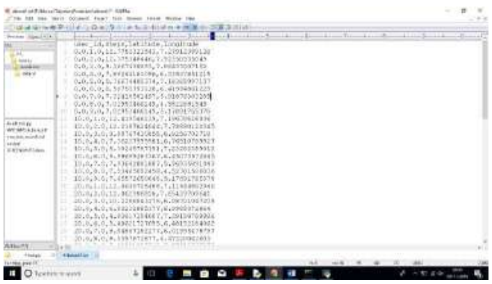
In above screen we can see message as LSTM training process completed, to see complete LSTM model we can see black console. See below screen



In above black console we can see LSTM generation process and in below screen we can see it accuracy also

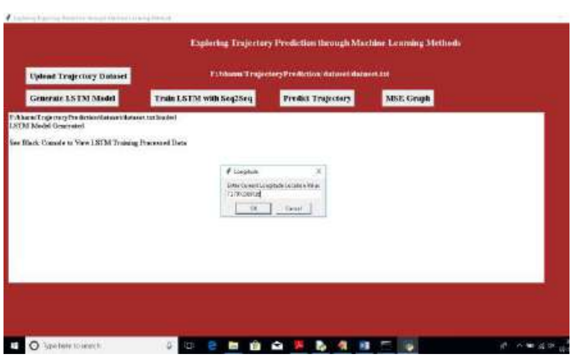


In above screen we can see LSTM with Seq2Seq got 94.44% accuracy. Now LSTM and Seq2Seq model is train and we can predict user's location by clicking on 'Predict Trajectory' button. After clicking on this button three dialogs boxes will appear which as users current latitude, longitude and user_id to predict next sequences. This details we can give from dataset and dataset has all this details. For example see below dataset values



In above dataset we have user_id, steps, latitude and longitude from this we can input any details. See below screen to give input

Similarly next we need to input longitude also



Next we need to input user_id for which user we are predicting location, In above screen I am giving first row values as input so user_id will be 0

After giving above input details we will get next predicted sequences

In above screen we got next locations latitude and longitude values from above output values u can ignore all zeroes and see only latitude and longitude values as users next predicted sequences locations. Now click on 'MSE Graph' to get Mean Square Error Graph between LSTM and Existing GRU technique

In above graph we can see with LSTM less prediction error is there compare to existing technique. In above graph x-axis contains algorithm name and y-axis contains error rate

V. CONCLUSION

In the age of 5G and edge computing, accurately predicting the next location of a user is critical for efficient network resource allocation and improved mobile application performance. Traditional methods such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) struggle to scale effectively with large datasets. To address this, the project introduces a predictive framework using Recurrent Neural Networks (RNN), specifically Long Short-Term Memory (LSTM) networks enhanced with Seq2Seq architecture. LSTM networks are capable of retaining important data from previous time steps, while Seq2Seq models provide a robust method for generating future sequences. The project is implemented using the Geolife dataset, which includes sequences of latitude and longitude data from multiple users. This approach enables real-time trajectory forecasting, contributing to advancements in smart navigation, traffic management, and next-gen mobile services.

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